

The Fusion of HRV and EMG Signals for Automatic Gender Recognition during Stepping Exercise

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Abstract

In this paper, a new gender recognition framework based on fusion of features extracted from healthy people electromyogram (EMG) and heart rate variability (HRV) during stepping activity using a stepper machine is proposed. An approach is investigated for the fusion of EMG and HRV which is feature fusion. The feature fusion is carried out by concatenating the feature vector extracted from the EMG and HRV signals. A proposed framework consists of a sequence of processing steps which are preprocessing, feature extraction, feature selection and lastly the fusion. The results shown that the fusion approach had improved the performance of gender recognition compared to solely on EMG or HRV based gender identifier.

Keywords: *gender recognition, feature fusion, heart rate variability (HRV), electromyography (EMG), Sstepper*

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1. Introduction

Automatic gender recognition plays an essential role in recognition of an individual. Gender recognition can help adequately to reduce the search time by constraining the further seeking stage to either a male or female database. Any appropriate biosignal trait can be utilized for further classification once a person is recognized as male or female. Automatic recognition of gender can also give an imperative sign in various security, surveillance and rehabilitation based applications.

Gender is known to affect HRV [1, 2] and EMG [3, 4]. Several studies have analyzed gender differences in autonomic adjustments in autonomic control following during exercise [5], [6]. Ahamed *et al.*, examined gender-related changes in the biceps brachii muscle by EMG signal analysis [4]. They found that the male subjects produced a higher and steadier signal than the female subjects. More recently, our previous work had explored the HRV response during short-term exercise by stair stepper machine [2]. The paper also makes a comparison of the finding significant HRV features between young healthy male and female and showed that there exist a significant gender difference in HRV features during short-term stepping exercise.

Furthermore, there are many different techniques for solving the problem of gender recognition such as based on fusion of face and gait information [7], fusion of facial strips [8], color information [9], sift features [10], fusion of different spatial scale features elected by mutual information from the hyhistogram of LBP (local binary patterns), intensity, and shape [11]. Plus, there are also techniques based on gabor filters combined with binary features [12], using a hybrid of gabor filters and local binary patterns to draw out face features and use self-organized map (SOM) for classification [13]. Next, there are methods based on extraction of the hip joint data that was computed from the Biovision Hierarchical data [14] and from gait sequences with arbitrary walking directions [15]. Moreover, it is true that physiological signals are also able to be implemented in gender classification. Thus, the physiological signals which are EMG and HRV signals collected during stepping activity are utilized in this research. But, there is not strong

enough classification results to identify gender if using only one physiological signal. Hence, the information from both EMG and HRV is combined together to get better classification result.

This paper considers the fusion of EMG and HRV signals from the same stepping sequence to carry out gender recognition and the feature fusion is used in order to compare the performance of the combination of EMG and HRV at this level. To the best of our knowledge this is the first method to combine EMG with the HRV for automatic gender recognition during short-term stepping exercise using a stepper. After that, the ongoing work can be used in order to support the interface system of the controllable current-induced stepper in rehab application. This paper is a further research on [2] and part of an effort to use information take out from the different physiological signals to design a robust and reliable automatic system to assess gender and develop less monitoring lower limb rehabilitation system [16], which may help to isolate male and female subjects to undergo rehabilitation process. It seems that the gender factor motivates people differently, in performing regular exercise for rehab.

2. Research Method

The proposed young gender recognitions are composed of a sequence of processing steps as described in the following sections.

2.1. Data Acquisition

The study was done in the Faculty of Biomedical and Health Science Engineering, Universiti Teknologi Malaysia, Johor Bahru. This study was done on 10 healthy, untrained young volunteers (mean 23.9 years, range 25 to 30). Of 10, 5 were male and 5 were female subjects. All subjects were free from any disease and explained about the procedures and their informed consent was taken.

The TMSi DAQ was used to record the EMG and ECG signals synchronously for gender assessment during exercise using stepper machine. The TMSi DAQ was utilized with three pairs of active surface electrodes and a single reference surface electrode to measure the electrical signals from the muscle and cardio. These surface electrodes are circular in shape (diameter = 11.4 mm) and are composed of silver/silver chloride (Ag/AgCl) material. The stepper machine was used to perform a stepping activity in order to generate the electrical activity of the muscle and heart (see Figure 1). Metronome (45 beat per minute) was used to fix the stepping rate. A metronome is a device used by musicians that indicates time at a selected rate by giving a regular tick.

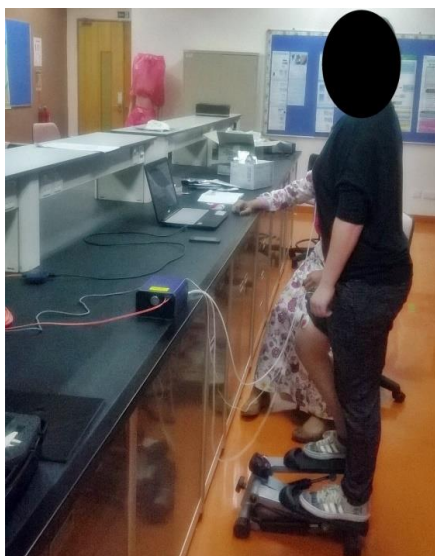


Figure 1. Experimental setup during stepping activity for EMG and ECG data acquisition [2]

2.2. Preprocessing

ECG: The ECG pre-processing and HRV quantification is implemented by using the Kubios HRV software [17]. Kubios HRV is progressive and convenient to utilize the software for HRV analysis. Moreover, the software supports a few input information for ECG data and RR interval (RRI) data. It contains an adaptive QRS detection algorithm and tools for artifact correction, trend removal and analysis sample selection.

The R-wave is automatically recognized by applying an assembled QRS detection algorithm in ECG data processing using Kubios. Basically, the Pan-Tompkins algorithm is utilized for the QRS detection algorithm in the Kubios software [18]. The preprocessing part contains bandpass filtering of the ECG, squaring of sample data and moving average filtering. The function of the bandpass filtering is to reduce the powerline interference, baseline wander and other noise components. Highlight peaks and smooth, close by peaks is the function of the squaring and moving average filtering respectively.

There are about three minutes of ECG signal recording is required for HRV signal analysis under normal physical and mental circumstances. Basically, the resultant signal is the HRV which is used in this study.

EMG: The EMG was filtered using a lowpass filter and highpass filter with a cutoff frequency of 20Hz and 300Hz respectively. The synchronization of EMG and HRV (see Figure 2) are required to achieve the combination between two modalities as explained later.



Figure 2. The synchronization of EMG and HRV

2.3. Feature Extraction

This section describes in brief the analysis parameters included in the Kubios software for HRV and analysis parameters for EMG.

2.3.1. HRV Features

The measurements and the notations used are basically based on the guidelines given in [19]. HRV features were extracted from time domain, frequency domain and non-linear generated from the Kubios Software as shown in the Figure 3.

Time domain features: The mean of RR interval (ms), standard deviation of RR (SDNN (ms)), mean of heart rate (HR (1/min)), SD of HR (1/min), RMSSD (ms), NN50 (count), pNN50 (%), HRV Triangular Index and TINN (ms).

Frequency Domain - Fast Fourier Transform (FFT) spectrum: The very low frequency (VLF (Hz)) peak, low frequency (LF (Hz)) peak, high frequency (HF (Hz)) peak, VLF power (ms^2), VLF power (%), LF power (ms^2), LF power (%), LF power (n.u.), HF power (ms^2), HF power (%), HF power (n.u.), ratio of LF and HF (ms^2) and total power (ms^2).

Frequency Domain - Autoregressive (AR) spectrum: The VLF peak (Hz), LF peak (Hz), HF peak (Hz), VLF power (ms^2), VLF power (%), LF power (ms^2), LF power (%), LF power (n.u.), HF power (ms^2), HF power (%), HF power (n.u.), ratio of LF and HF (ms^2) and total power (ms^2).

Nonlinear: The poincare plot (SD1 (ms) & SD2 (ms)) where SD1 and SD2 is the standard descriptors, approximate entropy (Apen), sample entropy (Sampen), correlation dimension, Detrended Fluctuation Analysis (DFA (alpha 1 & alpha 2)), recurrence plot (Lmean

(beats), Lmax (beats) where Lmax is the length of the longest line of recurrence point in a continuous row within the recurrence plot and Lmean is a mean line length, recurrence rate (REC (%)), determinism (DET (%)) and shannon entropy (Shanen).



Figure 3. Kubios software for HRV

2.3.2. EMG Features

EMG features were extracted from time domain and frequency domain as follows: **Time domain features:** The mean, standard deviation (SD), root mean square (RMS), variance, skewness and kurtosis. **Frequency domain features:** The mean frequency and mid frequency.

2.3.3. Feature Selection

The accuracy of the classification process may adversely affect if some of redundant irrelevant features of the features extracted are not appropriately eliminating [20, 21]. Hence, the feature selection method is applied, which is the wrapper method developed in [20, 21] using Weka in order to pick out an optimal feature subset of EMG and HRV with minimum redundancy and maximum class discriminability from the big extracted set. If the dimensionality of the feature set is decreased while the precision of the classification is either improved or stay unaffected, the feature selection is viewed as successful.

2.3.4. Feature Fusion of EMG and HRV during Short-Term Stepping Activity by Stepper

The proposed framework for feature fusion of EMG and HRV is shown in Figure 4. As represented in the figure, the EMG and HRV windows were preprocessed before implementing feature extraction processes. From the huge set of features extracted, a feature subset was selected using the wrapper-based feature selection method [20]. Then, The resulting feature vector F_{EMG} and F_{HRV} were concatenated to form a single composite feature vector, F_C , given by

$$F_C = [F_{EMG} | F_{HRV}] \quad (1)$$

The composite feature vector was then applied to a number of statistical classifiers. The explored classifiers for the feature fusion process were: Decision Tree (J48), NB (Naïve Bayes) and k -NN (k -Nearest Neighbors) with $k = 1, 3$ and 5 . The results are demonstrated in section 3.

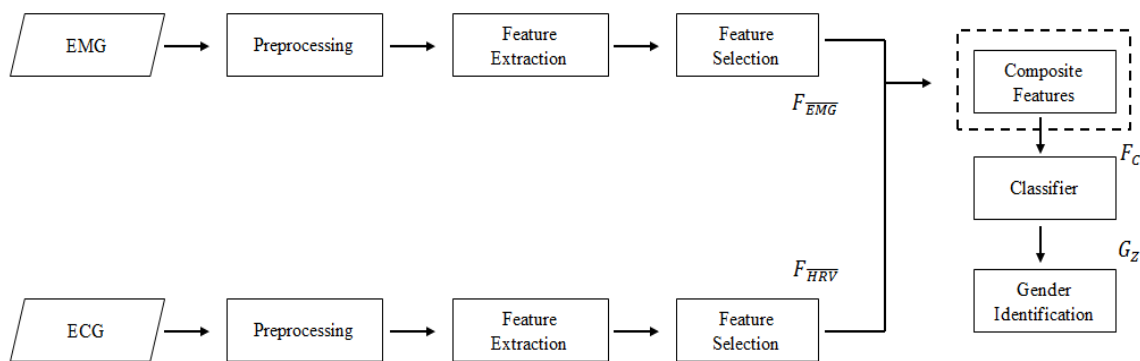


Figure 4. Automatic gender *recognition* process based on EMG-HRV feature fusion

3. Performance Analysis and Discussion

The performance of the EMG-HRV feature fusion process, as determined by the classification results, is shown in Figure 5. The figure shows that the 1-NN and 5-NN gives the best overall performance in identifying gender during short term stepping exercise by stepper machine. Both 1-NN and 5-NN classifiers achieved 80% sensitivity and almost 100% specificity.

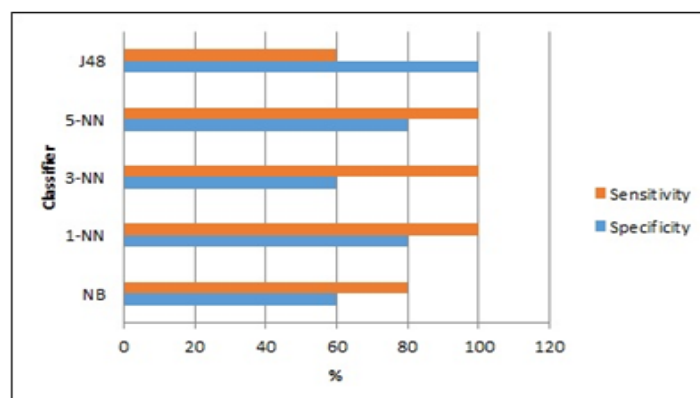


Figure 5. Performance of different classifier for gender assessment during short-term stepping exercise based on EMG and HRV features fusion

To assess the additional estimation of the proposed classification approach for gender recognition, their performances are compared to those based on either EMG or HRV. Table 1 shows the performances of 1-NN classifiers in terms of sensitivity (SEN) and specificity (SPE). The feature-based combination classifier achieved 80% SEN and almost 100% SPE compared to 60% SEN and 60% SPE using the EMG features alone and 80% SEN and 60% SPE using the HRV features only. Table 2 shows the performances of 5-NN classifier in terms of SEN and SPE too. The feature-based combination classifier achieved 80% SEN and almost 100% SPE compared to 40% SEN and 80% SPE using the EMG features alone and 80% SEN and 80% SPE using the HRV features only.

This shows that the combined features for 1-NN have significantly improved the SPE (+40%) of gender recognition during short-term stepping exercise by stepper machine compared to SPE achieved using either EMG or HRV features alone. The improvement of SEN through feature fusion, although not as dramatic as the SPE, was remarkable (+20% using EMG alone and +0% using HRV alone). Meanwhile, the combined features for 5-NN have significantly improved the SPE (+20%) of gender recognition during short-term stepping

exercise by stepper machine compared to SPE achieved using either EMG or HRV features alone. Also, the improvement of SEN through feature fusion, although not as dramatic as the SPE, was remarkable (+40% using EMG alone and +0% using HRV alone). Thus, from the discussion above, the 1-NN classifier is better performance compared to 5-NN classifier.

Furthermore, this paper also improves the gender recognition results compared to latest previous research. Das D obtained 76.79% gender recognition rate based on human gait using Support Vector Machine (SVM) [22], Archana GS [23] obtained 80% gender classification of speech performance using SVM and Hossain S [24] found 85% of male and 74% accurate decision based on the fingerprint based gender identification. This paper achieved 80% SEN and almost 100% SPE which is 90% gender correct rate using 1-NN classifier based on the fusion of HRV and EMG physiological signals.

Table 1. Performance comparison of gender recognition during short-term stepping exercise using a stepper machine from single signal classification (EMG/HRV) and the proposed fusion system for 1-NN classifier

EMG		HRV		Feature Fusion	
SEN (%)	SPE (%)	SEN (%)	SPE (%)	SEN (%)	SPE (%)
60	60	80	60	80	~ 100

Table 2. Performance comparison of gender recognition during short-term stepping exercise using a stepper machine from single signal classification (EMG/HRV) and the proposed fusion system for 5-NN classifier

EMG		HRV		Feature Fusion	
SEN (%)	SPE (%)	SEN (%)	SPE (%)	SEN (%)	SPE (%)
40	80	80	80	80	~ 100

4. Conclusion

An approach for the fusion of EMG and HRV signals acquired during short-term stepping activity by stepper machine were proposed in this paper. The fusion of the features extracted from EMG and HRV signals has prompted a better performing automatic gender recognition compared to solely on EMG and HRV signals. The outcomes affirmed that information from physiological signals that directly reflect neurological changes (using EMG) and signals that reflect autonomic behavior (using HRV) complement each other and their combination offers better gender recognition performance compared to solely on EMG and HRV. Gender factor encourages people differently in committing regular exercise for rehab. Therefore, this effort may help to isolate male and female subjects to experience rehabilitation process.

Acknowledgements

The work presented in this study is funded by Ministry of Education Malaysia and Universiti Teknologi Malaysia under research grant VOTE NO: 15H81.

References

- [1] Kattimani YR. Gender Comparison of Heart Rate Variability Response to Exercise in Male and Female Medical Students. *International Journal of Scientific Study*. 2015; 3(1): 48-53.
- [2] Rosli NAIM, Rahman MAA, Malarvili MB, Komeda T, Mazlan SA, Zamzuri H. The Gender Effects of Heart Rate Variability Response During Short-Term Exercise Using Stair Stepper from Statistical Analysis. *Indonesian Journal of Electrical Engineering and Computer Science*. 2016; 2(2): 359-366.
- [3] Carneiro JG, Goncalves EM, Camata TV, Altimari JM, Machado MV, Batista AR, Guerreiro JG, Moraes AC, Altimari LR. Influence of Gender on the EMG Signal of the Quadriceps Femoris Muscles and Performance in High-Intensity Short-Term Exercise. *Electromyography and Clinical Neurophysiology*. 2010; 50(7-8): 326-332.

- [4] Ahamed, NU, Yusof ZM, Alqahtani M, Altwijri O, Matiur Rahman SAM, Sundaraj K. Gender Effects in Surface Electromyographic Activity of the Biceps Brachii Muscle During Prolonged Isometric Contraction. *Procedia Computer Science*. 2015; 61: 448-453.
- [5] Carter JB, Banister EW, Blaber AP. Effect of Endurance Exercise on Autonomic Control of Heart Rate. *Sports Medicine*. 2003; 33(1): 33-46.
- [6] Huang WL, Chang LR, Kuo TBJ, Lin YH, Chen YZ, Yang CCH. Gender Differences in Personality and HeartRate Variability. *Psychiatry Research*. 2013; 209(3): 652-657.
- [7] Zhang D, Wang YH. *Gender Recognition Based on Fusion of Face and Gait Information*. Proceedings of Seventh International Conference on Machine Learning and Cybernetics, Kunming. 2008: 62-67.
- [8] Lee PH, Hung JY, Hung YP. *Automatic Gender Recognition Using Fusion of Facial Strips*. International Conference on Pattern Recognition. 2010: 1140-1143.
- [9] Lin GS, Zhao YJ. *A Feature-Based Gender Recognition Method Based on Color Information*. First International Conference on Robot, Vision and Signal Processing, Kaohsiung. 2011: 40-43.
- [10] Zahedi M, Yousefi S. Gender Recognition Based on Sift Features. *International Journal of Artificial Intelligence and Applications*. 2011; 2(3): 87-94.
- [11] Tapia JE, Perez, CA. Gender Classification Based on Fusion of Different Spatial Scale Features Selected by Mutual Information From Histogram of LBP, Intensity, and Shape. *IEEE Transactions on Information Forensics and Security*. 2013; 8(3): 488-499.
- [12] Barani, MJ, Faez K, Jalili F. Implementation of Gabor filters Combined with Binary Features for Gender Recognition. *International Journal of Electrical and Computer Engineering*. 2014; 4(1): 408-115.
- [13] Nazarloo M, Parcham E, Pourani RA. Gender Classification Using Hybrid of Gabor Filters and Binary Features of an Image. *International Journal of Electrical and Computer Engineering*. 2014; 4(4): 539-547.
- [14] Ali S, Zhou M, Wu Z, Razzaq A, Hamada M, Ahmed H. Comprehensive Use of Hip Joint in Gender Identification Using 3-Dimension Data. *TELKOMNIKA*. 2013; 11(6): 2933-2941.
- [15] Lu J, Wang G, Moulin P. Human Identity and Gender Recognition From Gait Sequences With Arbitrary Walking Directions. *IEEE Transactions on Information Forensics and Security*. 2014; 9(1): 51-61.
- [16] Rosli NAIM, Rahman MAA, Mazlan SA, Zamzuri H. *Electrocardiographic (ECG) and Electromyographic (EMG) Signals Fusion for Physiological Device in Rehab Application*. 2014 IEEE Student Conference on Research and Development, Batu Feringghi. 2014: 1-5.
- [17] Tarvainen MP, Niskanen JP. Kubios HRV - Heart Rate Variability Analysis Software. *Computer Methods and Programs in Biomedicine*. 2014; 113(1): 210-220.
- [18] Pan J, Tompkins WJ. A Real-Time QRS Detection Algorithm. *IEEE Transactions on Biomedical Electrophysiology*. 1985; 32(3): 230-236.
- [19] Task Force of The European Society of Cardiology and The North American Society of Pacing Electrophysiology. Heart Rate Variability: Standards of Measurement, physiological Interpretation, and Clinical Use. *Circulation*. 1996; 93(5): 1043-1065.
- [20] Malarvili MB, Mesbah M, Boashash B. *HRV Feature Selection for Neonatal Seizure Detection*. IEEE International Conference on Signal Processing and Communications, Dubai. 2007: 864-867.
- [21] Malarvili MB, Mesbah M, Boashash B. *HRV Feature Selection Based on Discriminant and Redundancy Analysis for Neonatal Seizure Detection*. 6th International Conference on Information, Communications and Signal Processing, Singapore. 2007: 1-5.
- [22] Das D, Chakrabarty A. *Human Gait Based Gender Identification Syatem Using Hidden Markov Model and Support Vector Machine*. International Conference on Computing, Communication and Automation, Greater Noida. 2015: 268-272.
- [23] Archana GS, Malleswari M. *Gender Identification and Performance Analysis of Speech Signals*. Proceedings of 2015 Global Conference on Communication Technologies, Thuckalay. 2015: 483-489.
- [24] Hossain MS, Habib MA. *Improving Fingerprint Based Gender Identification Technique Using Systematic Pixel Counting*. 2nd International on Electrical Engineering and Information & Communication Technology, Dhaka. 2015: 1-4.